Intelligent Ocean Navigation and Fuzzy-Bayesian Decision/Action Formulation

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***Abstract*—This paper focuses on the formulation of a decision–action execution model that can facilitate intelligent collision avoidance features in ocean navigation systems, while respecting the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) rules and regulations of collision avoidance. The decision/action process in this work consists of a fuzzy-logic-based parallel decision-making (PDM) module whose decisions are formulated into sequential actions by a Bayesian-network-based module. Therefore, the paper presents a collision avoidance system (CAS) that is capable of making multiple parallel collision avoidance decisions regarding several target vessel collision conditions, and those decisions are executed as sequential actions to avoid complex collision situations in ocean navigation.**

***Index Terms*—Bayesian network, fuzzy logic, intelligent transportation, intelligent vehicle control, marine vehicle control, ship collision avoidance.**

I. Introduction

INTELLIGENT decision formulation and action execution capabilities are important functionalities as well as major challenges in autonomous navigation systems. The development of computer technology, satellite communicational systems, and electronic devices, including high-tech sensors and actuators, have facilitated the integration of some autonomous features into land and air navigation systems. However, similar features in ocean navigation systems are still underdeveloped. In conventional ocean navigation systems, the most important factor is still human guidance, and wrong judgment and miss operations by humans have resulted in many human casualties and environmental disasters.

This phenomenon is supported by the reported data that show ship collisions as one of the important causes of maritime accidents [1]. The studies of maritime collisions [2], [3] indicate that 75%–96% of marine accidents and causalities are caused by some types of human errors. Therefore, as illustrated by e-Navigation [4], the implementation of intelligent autonomous capabilities into navigation systems and the limitation of human subjective factors in navigation could increase maritime safety and security. Further, the replacement of human inference by an intelligent decision formulation process resulting in feasible actions for navigation and collision avoidance could reduce maritime accidents and their respective causalities.

Theoretically, all vessels should follow the law of the sea while trying to avoid collision situations. The current law of the sea was formulated by the International Maritime Organization (IMO) in 1972 by the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) [5]. The present convention was designed to update and to replace the Collision Regulations, which were adopted at the same time as the International Convention for Safety of Life at Sea (SOLAS) Convention [6]. However, the reported data of maritime collisions presented in [7] show that 56% of major maritime collisions involve violation of the COLREGs rules and regulations.

The COLREGs includes 38 rules that are divided into Part A (General), Part B (Steering and Sailing), Part C (Lights and Shapes), Part D (Sound and Light Signals), and Part E (Exemptions). There are also four Annexes containing technical requirements concerning lights and shapes and their positioning, sound signaling appliances, additional signals for fishing vessels while operating in close proximity, and international distress signals.

The maintenance of safe distance among vessels and other obstacles is the most important factor for improving maritime safety. However, the maintenance of continuous safe distance between two vessels is also an important factor to reduce the risk of collisions in overtake and head-on situations. Therefore, the safe distance maintenance by both vessels in overtake and head-on situations is also emphasized in the COLREGs [rule 13(a)].

The crossing of two vessels is another distinct situation involving high collision risk in ocean navigation. As required by the COLREGs, the vessels should take early actions to avoid situations of crossing ahead with the risk of collision in starboard to starboard and must be passing by port to port. These crossing situations are illustrated in the COLREGs (rule 15). As specified by the COLREGs, the vessel coming from the starboard side has higher priority for the navigation and is referred to as the "stand on" vessel. The vessel coming from the port side has lower priority for navigation and is referred to as the "give way" vessel.

When considering the collision conditions where the "give way" vessel does not take any appropriate actions to avoid collision as required by the COLREGs [rule 17(b)], the "stand on" vessel is forced to take appropriate actions to avoid the

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collision situation. However, the decision-making process of the "stand on" vessel in these critical collision situations should be carefully formulated since the collision avoidance alternatives depend on the "stand on" vessel maneuverability characteristics. Further, these situations might lead to the "crash stopping" maneuver of the "stand on" vessel due to a lack of distance for speed reduction. The characteristics of the "stand on" vessel with respect to the "stopping distance" and the "turning circle" should therefore be considered for formation of the decisions in collision avoidance. Further, the vessel course and/or speed changes in ocean navigation must be executed to avoid collision situations at any cost, as highlighted in the COLREGs [rule 8(b)].

However, the COLREGs rules and regulations are further interpreted by the respective judicial authorities of the maritime regions after the vessel collision or near-collision situations. A detailed description with a difference of interpretation of the COLREGs rule and regulations on autonomous ocean navigation is presented in [8].

It is a fact that the COLREGs rules and regulations regarding collision situations in ocean navigation are ignored in most recent studies regarding collision avoidance. However, the methods that ignore the COLREGs rules and regulations should simply not be implemented in ocean navigation since they generate conflict situations with other vessels that are supposed to follow them.

On the other hand, there are some practical issues that hinder the implementation of the COLREGs rules and regulations in ocean navigation. For example, when the "target vessel" (i.e., the vessel that must be avoided in a collision situation) has a very low or very high speed when compared to the speed of the "own vessel" [i.e., the vessel equipped with the collision avoidance system (CAS)], the implementation of the COLREGs rules and regulations is questionable. Therefore, in addition to the COLREGs rules and regulations, expert knowledge in navigation should also be considered in the formulation of navigation decisions of collision avoidance, as proposed in this study.

This paper focuses on the formulation of a decision/action execution process that can facilitate the intelligent collision avoidance features into ocean navigation systems while respecting the COLREGs rules and regulations, which is a further development of the intelligent navigation system presented in [9]–[13]. The decision/action process in this work consists mainly of a fuzzy-logic-based parallel decision-making (PDM) module whose decisions are formulated into sequential actions by a Bayesian-network-based module. Further, the paper presents a CAS capable of making multiple parallel collision avoidance decisions regarding several target vessels. These decisions are executed as sequential actions to avoid complex collision situations in ocean navigation.

The organization of this paper is as follows. Section II contains an overview of previous related work. Section III formulates the problem of collision avoidance in ocean navigation systems. A fuzzy-logic-based PDM module is presented in Section IV and a Bayesian-network-based sequential action formulation module is described in Section V. Section VI contains a detailed description of implementation and computational simulations. Finally, conclusions and future work are presented in Section VII.

II. Previous Related Work

The main functionalities of autonomous ocean navigation systems are summarized by Fossen [14]. Some of the concepts highlighted in this study are course-keeping and course-changing maneuvers, integration of digital data, dynamic position, and automated docking systems. Similarly, recent developments of autonomous ocean navigation systems are also summarized in [15]. Due to the navigation cost reduction and the improvements of maritime safety and security, this area is bound to become increasingly important in the future of ocean navigation, as also illustrated in [16].

A decision-making process and strategies in interaction situations in ocean navigation, including avoidance of collision situations, are presented in [17]. The analysis of quantitative data describing the maneuvers undertaken by ferries and cargo ships and behavior of the "give way" vessel and the "stand on" vessel with respect to verbal reports recorded onboard a car ferry in the Dover Strait are also summarized in the same work.

The collision risk evaluation is ultimately influenced by the prediction and estimation process of the target vessel (the vessel to be avoided) trajectory. Hence, the detection of the target vessel position, velocity, and acceleration are the most important factors in this assessment process. Sato and Ishii [18] proposed combining radar and infrared imaging methods to detect the target vessel position conditions as a part of the CAS. The same study proposes to assess collision risk by taking the course measurements of the target vessel determined by image processing. However, in close encounter situations, an accurate estimate of the target vessel's position, velocity, and acceleration was not possible when the own vessel (i.e., the vessel equipped with the collision avoidance capabilities) depended only on radar and infrared imaging. This could happen due to the inaccuracy in the distance measurements in radar systems in close encounters as well as errors in the image analysis process.

The size and the shape of the own vessel domain, which can be defined as the area bounded for the dynamics of the marine vessel, are important factors to assess the collision risk in ocean navigation. Lisowski *et al.* [19] used neural classifiers to support the navigator in the process of determining the vessel's domain, defining that the area around the vessel should be free from stationary or moving obstacles. On a similar approach, Pietrzykowski and Uriasz [20] proposed the notion of vessel domain in a collision situation as depending on the parameters like vessel size, course, and heading angle of the encountered vessels. A fuzzy-logic-based domain determination system is also considered in the same work, but deterministic vessel domain conditions are assumed during the collision risk evaluation process in this study.

Kwik [21] presented collision risk calculations for a two-ship collision encounter based on the kinematics and dynamics of marine vessels. Even though the results of collision avoidance analysis are illustrated regarding the vessel velocity, the turning rate and the direction, and the desire passing distance, the study is limited to a two-vessel collision situation. Yavin *et al.* [22] considered the collision avoidance conditions of a ship moving from one point to another in a narrow zigzag channel proposing a computational open-loop command strategy for the rudder control system. However, since most of the restricted waters and channel navigation regions are associated with specific rules and regulations, the flexibility of this approach is rather limited.

The design of a safe ship trajectory is an important part of the collision avoidance process and has normally been simulated by mathematical models based on maneuvering theory [23]. An alternative approach based on neural networks is also proposed by Moreira and Guedes Soares [24]. Smierzchalski and Michalewicz [25] modeled safe ship trajectory in navigation using an evolutionary algorithm and considering static and dynamic constrains for the optimization process.

Ito *et al.* [26] used a genetic algorithm to search for safe trajectories on collision situations in ocean navigation. The approach is implemented in the training vessel of "Shiojimaru" integrating automatic radar plotting aids (ARPAs) and differential global positioning system (DGPS). ARPA system data are also formulated as a stochastic predictor in this study. Furthermore, in [27], a Markov process is used to derive the *a priori* probability density map of the existence of obstacles in the same experimental setup. Hong *et al.* [28] presented a collision-free trajectory in ocean navigation based on a recursive algorithm that is formulated by analytical geometry and convex set theory. Similarly, Cheng *et al.* [29] have presented trajectory optimization for ship CAS based on a genetic algorithm.

Even though these optimization algorithms always find the optimum solutions for the safest trajectories (based on assumptions), the optimum solutions may not be realistic and do not necessarily present intelligent features. As an example, it is observed that some of the optimization algorithms always find the safest path behind the target vessel. That might lead to a conflict situation with the COLREGs rules and regulations where the own vessel is in a "stand on" vessel situation. Further, the fact that the future behavior of the target vessel cannot be incorporated into the optimization algorithm is another disadvantage in this approach.

Computational intelligence is a research area that combines evolutionary algorithms, fuzzy logic, expert systems, and neural networks. Statheros *et al.* [7] give an overview of computational intelligence techniques that are used in collision avoidance in ocean navigation.

Liu and Liu [30] used case-based reasoning (CBR) to illustrate learning of collision avoidance techniques in ocean navigation by the recorded data of collision situations. In addition, a collision risk evaluation system that is based on a data fusion method is considered and fuzzy membership functions (FMFs) for evaluating the degree of risk are also proposed in the same study. Further, an intelligent anticollision algorithm for different collision conditions is designed and tested on the computer-based simulation platform in [31]. Zhuo and Hearn [32] presented a study of two-vessel collision avoidance in ocean navigation using a self-learning neurofuzzy-network-based online and offline training scheme. A Sugeno-type fuzzy inference system is proposed for the decision-making process in the same study.

Fuzzy-logic-based systems, which are formulated for human-type thinking, facilitate a human friendly environment during the decision-making process. Hence, several decision-making systems in research as well as commercial applications have been presented before [33]. The human conjunction behavior, the human understanding of relationships among objects and/or situations, and the respective decision-making process are formulated by various fuzzy systems in [34] and [35].

A fuzzy logic approach for collision avoidance with the integration of a virtual force field is proposed by [36]. In this approach, the navigation system is kept away from the obstacles by repulsive force fields. This concept may not be practical in situations where the target vessel is moving with very low speed or very high speed when compared to the own vessel speed since the collision risk is negligible unless the vessels pass the collision junction simultaneously; therefore, no collision avoidance actions are required. However, the repulsive force fields approach still takes collision avoidance actions in the above described no-collision situation. In addition, complex orientations of obstacles and target vessels may lead to unavoidable collision situations in this method. On the other hand, repulsive-force-based optimization algorithms are enforced to find the global safe trajectory for the own vessel navigation, and this might not be a good solution for the localized trajectory search. Furthermore, the concepts of "give way" and "stand on" vessels that are introduced by the COLREGs rules and regulations are not taken into consideration during the repulsive-force-based optimization process. Therefore, this method may not honor the COLREGs rules and regulations during its optimization process.

An automatic collision avoidance facility for a ship system using a fuzzy-logic-based controller is proposed by [37], but, as above, the simulation results of this approach are limited to two-vessel collision avoidance situations and both the COLREGs rules and regulations and the expert knowledge in ocean navigation (i.e., crash stopping maneuvers) are neglected in this approach. One should also note that the target vessel speed conditions that might be useful in the collision risk evaluation process and the collision avoidance decision-making process are ignored in almost all of the proposed methods.

Benjamin *et al.* [38] proposed behavior-based controls formulated with interval programing for collision avoidance of ocean navigation. The collision avoidance behavior is illustrated in accordance with the Coast Guard Collision Regulations (COLREFGS-USA). In [39], Benjamin and Curcio present a decision-making process of ocean navigation based on an interval programing model for a multiobjective decision-making algorithm. The computational algorithm based on IF–THEN logic is defined and is tested under simulator conditions by Smeaton and Coenen [40] regarding different collision situations. Further, this study is focused on the rule-based maneuvering advice system for collision avoidance of ocean navigation. However, the IF–THEN rules are formulated in a single-step decision-making process in this study; where the rule failures can occur in navigation, as described in [41].

Cockcroft and Lameijer present in [6] a detailed description of the COLREGs rules and regulations, how to implement rules and regulations, and how the judicial authorities of the respective maritime regions interpret the rules and regulations after several vessel collision and near-miss situations. Furthermore, Benjamin and Curcio discuss [38] the complexities of autonomous navigation, not only in the sea but also on the ground. The legal framework of rules and regulations for

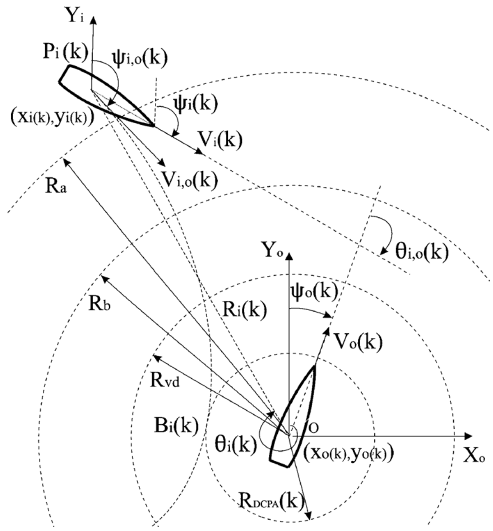

Fig. 1. Two-vessel collision situation.

ocean navigation and the importance of collision avoidance within a given set of formulated rules and regulations are also highlighted in the same work.

III. Collision Avoidance in Ocean Navigation

A. Two-Vessel Collision Situation

A two-vessel collision situation is presented in Fig. 1. The own vessel, the vessel that is equipped with the CAS (see Fig. 2), is located in the point $O(k)$ $(x_o(k), y_o(k))$, at the kth instant. The ith target vessel, the vessel that needs to be avoided, is located at point $P_i(k)$ $(x_i(k), y_i(k))$, with the estimated relative navigation trajectory of $P_i\ (k)B_i(k)$. The target vessel estimated relative trajectory $P_i(k)B_i(k)$ will intercept the own vessel domain with the closest points of $B_i(k)$. Therefore, the closest distance between the vessels in a collision situation is represented as $R_{\rm DCPA}(k)$. The own vessel speed and course conditions are represented by $V_o(k)$ and $\psi_o(k)$; the ith target vessel speed and course conditions are represented by $V_i(k)$ and $\psi_i(k)$; the ith target vessel bearing and relative bearing conditions are represented by $\theta_i(k)$ and $\theta_{i,o}(k)$; the relative speed and course conditions of the ith target vessel are represented by $V_{i,o}(k)$ and $\psi_{i,o}(k)$. All angles are measured with respect to the positive Y-axis.

A mathematical formulation of a two-vessel collision situation is further illustrated in Fig. 3. The own vessel navigation space is divided into three circular regions with radius R_{vd}, R_b, and R_a. The radius R_a represents the approximate range to the target vessel detection when the own vessel is in a "give way" situation, i.e., when the own vessel has low priority for navigation and should take appropriate actions to avoid collision situations. The radius R_b represents the approximate distance to the target vessel, when the own vessel is in a "stand on" situation with the higher priority for navigation and should take appropriate actions to avoid collision due to absence of the appropriate actions from the target vessel. The radius R_{vd} represents the vessel domain. These regions are separated by the dotted circles that coincide with the range FMFs (see Fig. 4). Finally, $R_i(k)$ represents the range of the ith target vessel at kth instant.

The own vessel navigation domain is divided into ten regions from I to X (see Fig. 3). These regions are separated by dotted straight lines that coincide with the regions of the bearing FMF (see Fig. 5). It is formulated that the target vessel should be located within these ten regions and the collision avoidance decisions are accumulated in accordance with the respective regions. The selection of the regions of the own vessel negation domain and their size considerations are further discussed in [42].

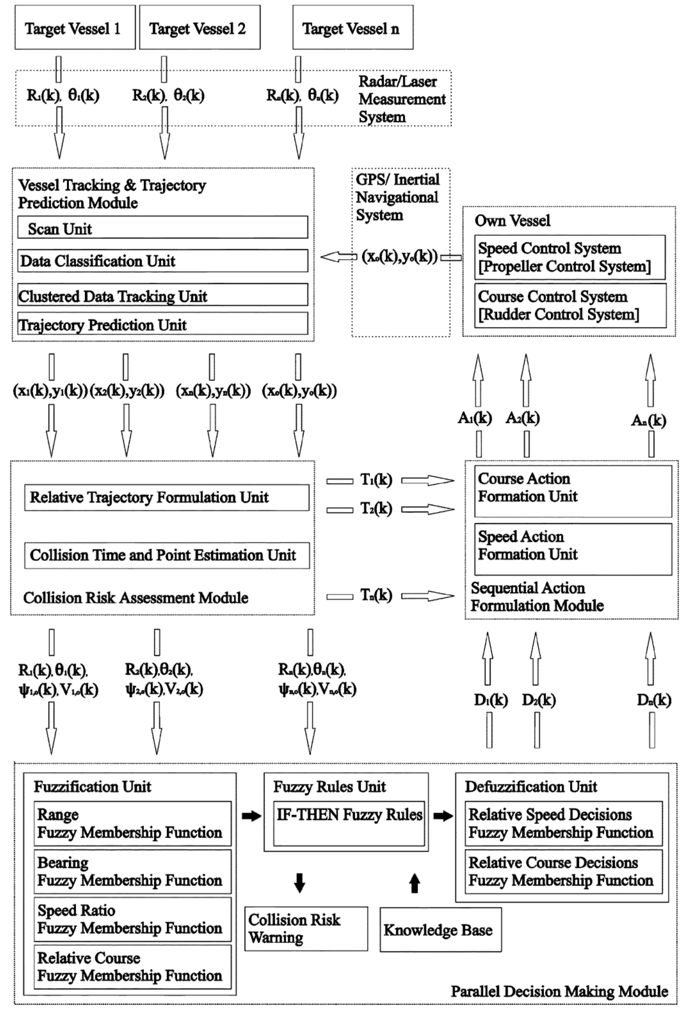

Fig. 2. Block diagram for CAS.

As presented in Fig. 3, the target vessel position II domain is divided into eight divisions (from II-a to II-h) of relative course $\psi_{i,o}(k)$ (see Fig. 1). These divisions are separated by the dotted lines that are coincidental with the relative course FMF (see Fig. 6). However, the higher collisions risk regions, mid and high collision risks, are only presented in the relative course FMF. In addition, the own and target vessels speed and course conditions are considered as $V_o(k), \psi_o(k)$, and $V_i(k), \psi_i(k)$, respectively. The speed ratio between the target vessel and the own vessel $V_i(k)/V_o(k)$ that coincides with the speed ratio FMF (see Fig. 7) is also estimated. One must note that this study assumes that the target vessel maintains constant speed and course conditions.

B. Multivessel Collision Situation

The expansion of a two-vessel collision situation into a multivessel collision situation is presented in Fig. 8. The own vessel is located at point $O(k)$. The target vessels are

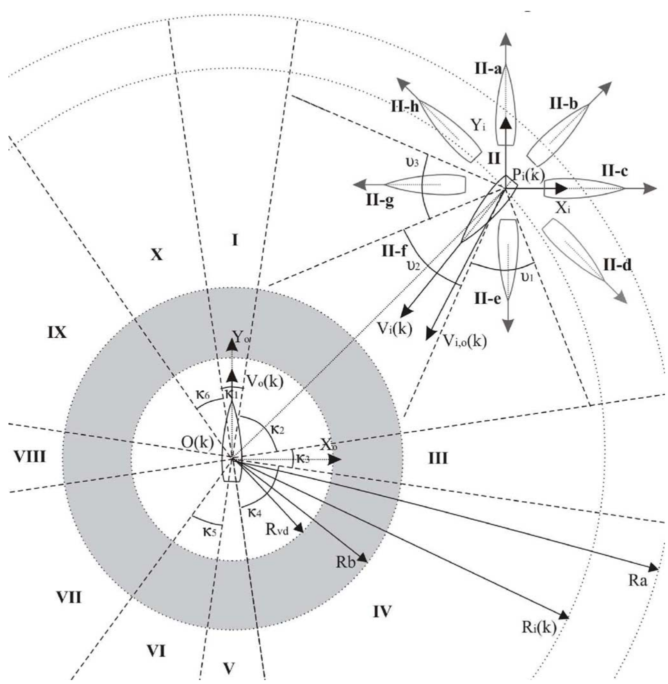

Fig. 3. Mathematical formulation of a two-vessel collision situation.

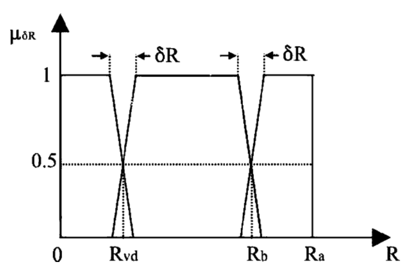

Fig. 4. Range FMF.

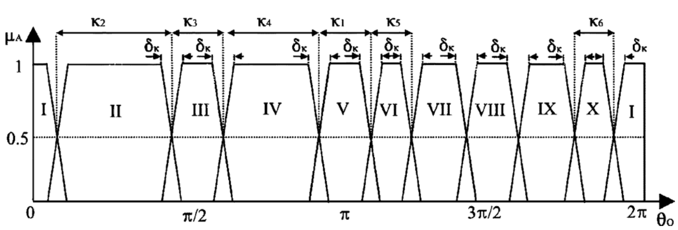

Fig. 5. Bearing FMF.

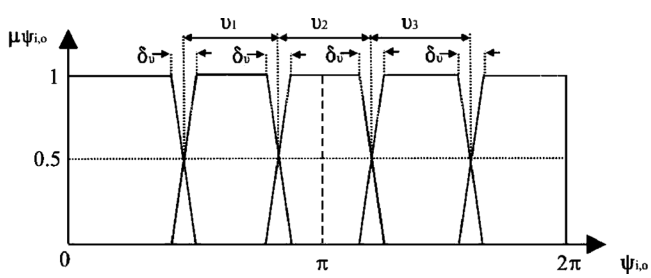

Fig. 6. Relative course FMF.

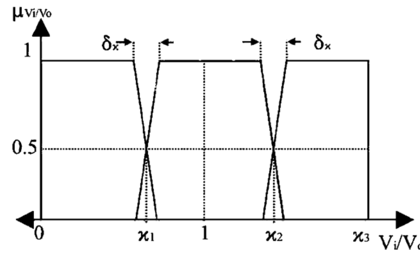

Fig. 7. Speed ratio FMF.

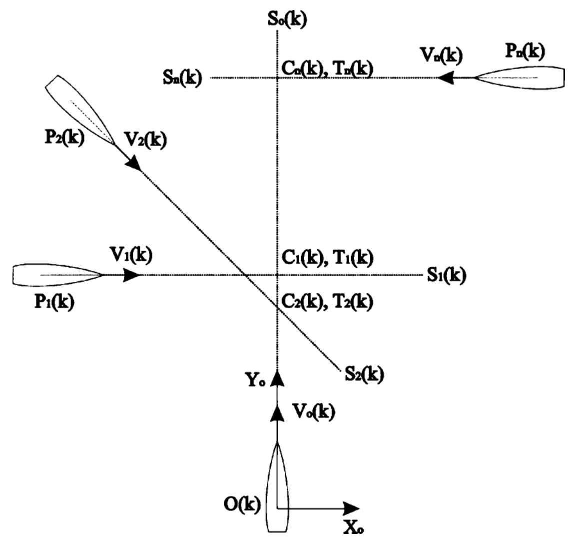

Fig. 8. A multivessel collision situation.

located at the points of $P_1(k), P_2(k), \ldots, P_n(k)$ with the navigation trajectories of $S_1(k), S_2(k), \ldots, S_n(k)$ at the kth instant, respectively. The own vessel trajectory $S_0(k)$ will intercept the trajectories $S_1(k), S_2(k), \ldots, S_n(k)$ around the points of $C_1(k), C_2(k), \ldots, C_n(k)$ at the instants of $T_1(k), T_2(k), \ldots, T_n(k)$, respectively.

C. Modules of Collision Avoidance System

A block diagram for complete CAS is presented in Fig. 2. The complete CAS consists of four modules: vessel tracking and trajectory prediction (VTTP) module, collision risk assessment (CRA) module, PDM module, and sequential action formation (SAF) module.

The inputs into the VTTP module are the real-time position of the own vessel $(x_o(k), y_o(k))$, that can be measured/estimated by GPS/inertial navigation systems, the Cartesian coordinates, and the real-time position of each target vessel's $(R_i(k), \theta_i(k))$ that is measured in polar coordinates. The range $(R_i(k))$ and bearing $(\theta_i(k))$ values of the ith target vessel can be obtained using radar/laser measurement systems by the kth instant.

The VTTP module consists of four units: scan unit, data classification unit, clustered data tracking unit, and trajectory prediction unit. The integrated radar/laser measurement system is considered for the scan unit where the real-time position data of the target vessels are collected. The target vessel's data are used in the data classification unit to identify each vessel and the clustered data tracking unit tracks each target vessel separately using these data. Finally, the collected tracking data are used to predict each target vessel's trajectory in the trajectory prediction unit. Due to the target vessel's constant speed and course conditions, this process is simplified in this study.

The main objective of the CRA module is to evaluate the collision risk of each target vessel with respect to the own vessel navigation. This is achieved by the relative trajectory formation unit and the collision time and point estimation unit. The inputs into the CRA module are the measured/estimated position data of the own vessel and target vessels. The outputs of the CRA module are range $(R_i(k))$, bearing $(\theta_i(k))$, relative course $(\psi_{i,o}(k))$, and relative speed $(V_{i,o}(k))$ of the ith target vessel. These outputs will be used as the inputs of the PDM module at the kth instant. In addition, the time until the collision situation $T_i(k)$ of the ith target vessel will input into the SAF module from the CRA module. The PDM module consists of a fuzzy-logic-based decision-making process that generates parallel collision avoidance decisions with respect to each target vessel at the kth instant.

As the next step, the parallel ith decision of collision avoidance $D_i(k)$ will move forward from the PDM module to the SAF module. The main objective of the SAF module is to organize the parallel decisions made by the PDM module into sequential actions $A_i(k)$, considering the time until the collision situation $T_i(k)$ that will be executed on the own vessel navigation. These actions are further divided into two categories of course and speed control actions that will be implemented on the propeller and rudder control systems of the own vessel.

IV. Parallel Decision-Making Module

An overview of the PDM module is also presented in Fig. 2. The module consists of three main units: fuzzification unit, fuzzy rules unit, and defuzzification unit.

A. Fuzzification Unit

Fuzzy sets are defined by FMFs, which can be described as mappings from one given universe of discourse to a unit interval. A fuzzy variable is usually defined by special FMFs called linguistic terms that are used in fuzzy-rule-based inference. The inputs from the CRA module, range $(R_i(k))$, bearing $(\theta_i(k))$, relative course $(\psi_{i,o}(k))$, and relative speed $(V_{i,o}(k))$ of the ith target vessel at the kth instant are fuzzified in this unit with respect to the input FMFs: range FMF $(R_i(k))$ (see Fig. 4), speed ratio FMF $(V_i(k)/V_o(k))$ (see Fig. 5), bearing FMF $(\theta_i(k))$ (see Fig. 6), and relative course FMF $(\psi_{i,o}(k))$ (see Fig. 7). Then, the fuzzified results from the fuzzification unit will transfer to the fuzzy rules unit for further analysis.

B. Fuzzy Inference and Rules

A Mamdani-type IF $\langle$antecedent$\rangle$ THEN $\langle$consequent$\rangle$ rule-based system is developed and inference via min–max norm is considered in the fuzzy rules unit. The IF–THEN fuzzy rules are developed in accordance with the COLREGs rules and regulations. However, the expert navigation knowledge is also considered in the fuzzy rules development process. Overtaking, head-on, and crossing are the three distinct situations that involve the risk of collisions in ocean navigation, which were considered for the development of the IF–THEN fuzzy rules.

The decision space of collision avoidance can be categorized into three stages for each vessel in an open ocean environment. When none of the vessels is at the collision risk range, both vessels have the option to take appropriate actions to avoid a collision situation. However, when both vessels are at the collision risk range, the "give way" vessel should take appropriate actions to achieve safe passing distance in accordance with the COLREGs rules and regulations, and the "stand on" vessel should maintain the course and speed conditions. Further, when both vessels are at the critical collision risk range, and the "give way" vessel does not take appropriate actions to achieve a safe passing distance in accordance with the COLREGs rules and regulations, then the "stand on" vessel has the option to take appropriate actions to avoid the collision. These concepts are further considered for the formulation of the fuzzy rules unit.

The negligence of the COLREGs rules and regulations may lead to conflicts during ocean navigation. However, in the case of near-collision situations in ocean navigation, the COLREGs rules do not facilitate clear guidance (i.e., rules and regulations). Therefore, expert navigation knowledge is also considered for the formation of the fuzzy rules in some collision situations.

Tables I and II present the summarized CRAs, fuzzy rules, and collisions avoidance decisions. The first column of Table I represents the bearing $\theta_i(k)$ (Bear.) of the target vessel, which is divided into ten regions (I–X). The second column represents the relative course $\psi_{i,o}(k)$ (Cou.), divided into eight regions (a–h) of the target vessel orientations. The collision risk (Risk) assessment with respect to the relative course of the target vessel is divided into three sections of low risk (Low), medium risk (Mid.), and high risk (High). However, the high and medium collision risk situations, where the collision avoidance actions must be executed, are only presented in Tables I and II. The target vessel ranges $(R_i(k))$ from R_{vd} to R_a and from R_a to R_b are presented in the third and fourth columns, respectively.

The third and fourth columns are further divided into two subcolumns. The relative speed ratio of $(V_i(k)/V_o(k))$ is presented in the first subcolumn of the third and fourth main columns. The speed conditions of V_i/V_o $<, \approx$ and >1 represent the target vessel speed approximately less than, equal, and greater than the own vessel speed.

Finally, the decisions that need to be taken to avoid collision situations are presented in the second subcolumn of the third and fourth columns. The decisions can be categorized as: course to starboard $\delta\psi_o > 0$; course to port $\delta\psi_o < 0$; no course change; increase speed $\delta V_o > 0$; decrease speed $\delta V_o < 0$; no speed change; and not applicable (NA). Table II is organized similarly.

C. Defuzzification

The collision avoidance decisions $D_i(k)$, for each target vessel are generated by the defuzzification unit. The fuzzy inference results from the previous unit are defuzzified based on the course change FMF (see Fig. 9) and the speed change FMF (see Fig. 10) to obtain the course change decisions $D_{\delta\psi i}(k)$ and the speed change decisions $D_{\delta V i}(k)$ that will be formulated for the collision avoidance actions in the own vessel navigation.

TABLE I
COLLISION RISK ASSESSMENTS, FUZZY RULES, AND DECISIONS

Bea	Cou./Risk	Range $(R_{vd}\,R_a)$		Range (R_aR_b)	
		$\frac{V_i}{V_o}$	Decision	$\frac{V_i}{V_o}$	Decision
I	d / Mid.	<1	NA	<1	NA
		≈ 1	NA	≈ 1	NA
		> 1	NA	> 1	NA
	e / High	<1	$\delta\psi_o>0$	<1	$\delta\psi_o>0$
		≈ 1	$\delta\psi_o>0$	≈ 1	$\delta\psi_o>0$
		> 1	$\delta\psi_o>0$	> 1	$\delta\psi_o>0$
	f / Mid.	<1	NA	<1	NA
		≈ 1	NA	≈ 1	NA
		> 1	NA	> 1	NA
II	e / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	$\delta V_o>0$
		> 1	$\delta V_o>0$	> 1	$\delta V_o>0$
	f / High	<1	NA	< 1	NA
		≈ 1	$\delta\psi_o>0, \delta V_o<0$	≈ 1	$\delta\psi_o>0, \delta V_o<0$
		> 1	$\delta\psi_o>0, \delta V_o<0$	> 1	$\delta\psi_o>0, \delta V_o<0$
	g / Mid.	<1	NA	<1	NA
		≈ 1	$\delta\psi_o>0$	≈ 1	$\delta\psi_o>0$
		> 1	$\delta\psi_o>0$	> 1	$\delta\psi_o>0$
III	f / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	$\delta V_o>0$
		> 1	$\delta V_o>0$	> 1	$\delta V_o>0$
	g / High	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	$\delta V_o<0$
		> 1	$\delta V_o<0$	> 1	$\delta V_o<0$
	h / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	$\delta V_o<0$
		> 1	$\delta V_o<0$	> 1	$\delta V_o<0$
IV	g / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	$\delta V_o>0$
		> 1	$\delta V_o>0$	> 1	$\delta V_o>0$
	h / High	<1	NA	<1	NA
		≈ 1	$\delta\psi_o<0, \delta V_o<0$	≈ 1	$\delta\psi_o<0, \delta V_o<0$
		> 1	$\delta\psi_o<0, \delta V_o<0$	> 1	$\delta\psi_o<0, \delta V_o<0$
	a / Mid.	<1	NA	<1	NA
		≈ 1	$\delta\psi_o<0, \delta V_o<0$	≈ 1	$\delta\psi_o<0, \delta V_o<0$
		> 1	$\delta\psi_o<0, \delta V_o<0$	> 1	$\delta\psi_o<0, \delta V_o<0$
V	h / Mid.	<1	NA	<1	NA
		≈ 1	NA	≈ 1	NA
		> 1	NA	> 1	NA
	a / High	<1	$\delta\psi_o<0$	<1	NA
		≈ 1	$\delta\psi_o<0$	≈ 1	NA
		> 1	$\delta\psi_o<0$	> 1	NA
	b / Mid.	< 1	NA	< 1	NA
		≈ 1	NA	≈ 1	NA
		> 1	NA	> 1	NA

NA = Not Applicable.

TABLE II
COLLISION RISK ASSESSMENTS, FUZZY RULES, AND DECISIONS

Bear.	Cou./Risk	Range $(R_{vd}\,R_a)$		Range (R_aR_b)	
		$\frac{V_i}{V_o}$	Decision	$\frac{V_i}{V_o}$	Decision
VI	a / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	NA
		> 1	$\delta V_o<0$	> 1	NA
	b / High	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	NA
		> 1	$\delta V_o<0$	> 1	NA
	c / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	NA
		> 1	$\delta V_o>0$	> 1	NA
VII	a / Mid.	<1	NA	<1	NA
		≈ 1	$\delta\psi_o>0$	≈ 1	NA
		> 1	$\delta\psi_o>0$	> 1	NA
	b / High	<1	NA	<1	NA
		≈ 1	$\delta\psi_o>0, \delta V_o<0$	≈ 1	NA
		> 1	$\delta\psi_o>0, \delta V_o<0$	> 1	NA
	c / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	NA
		> 1	$\delta V_o>0$	> 1	NA
VIII	b / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	NA
		> 1	$\delta V_o<0$	> 1	NA
	c / High	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	NA
		> 1	$\delta V_o<0$	> 1	NA
	d / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	NA
		> 1	$\delta V_o>0$	> 1	NA
IX	c / Mid.	<1	NA	<1	NA
		≈ 1	$\delta\psi_o<0$	≈ 1	NA
		> 1	$\delta\psi_o<0$	> 1	NA
	d / High	<1	NA	<1	NA
		≈ 1	$\delta\psi_o<0, \delta V_o<0$	≈ 1	NA
		> 1	$\delta\psi_o<0, \delta V_o<0$	> 1	NA
	e / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	NA
		> 1	$\delta V_o>0$	> 1	NA
X	c / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	NA
		> 1	$\delta V_o<0$	> 1	NA
	d / High	<1	NA	<1	NA
		≈ 1	$\delta V_o<0$	≈ 1	NA
		> 1	$\delta V_o<0$	> 1	NA
	e / Mid.	<1	NA	<1	NA
		≈ 1	$\delta V_o>0$	≈ 1	NA
		> 1	$\delta V_o>0$	> 1	NA

NA = Not Applicable.

The defuzzification process uses the center of gravity method. In this method, one calculates the centroid of the resulting FMF and uses its abscissa as the final result of the inference.

V. SEQUENTIAL ACTION FORMATION MODULE

A. Action Execution in Navigation

The main objective of the SAF module is to transform the parallel collision avoidance decisions that are generated by PDM module into sequential action formulation that can be executed in the own vessel navigation. This can be achieved by collecting the PDM module multiple collision avoidance decisions for the kth instant $D_i(k) \equiv (D_{\delta\psi i}(k), D_{\delta V i}(k))$ and evaluating them using the time until the collision situation $T_i(k)$ from the CRA module with respect to each target vessel.

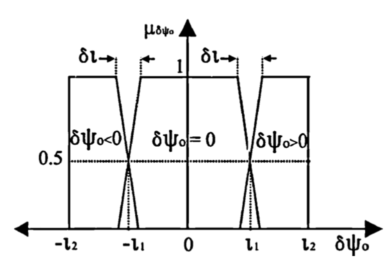

Fig. 9. Course change FMF.

Final results are arranged as a sequential formation of actions $A_i(k) \equiv (A_{\delta\psi i}(k), A_{\delta V i}(k))$ involving the course and speed actions at given instants $(T_{\delta\psi i}(k), T_{\delta V i}(k))$. Fig. 11 gives an example of the process of sequential course and speed action

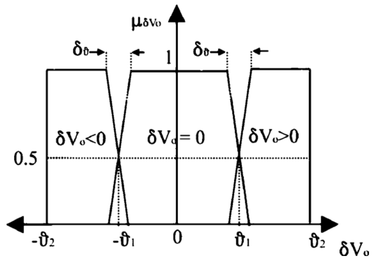

Fig. 10. Speed change FMF.

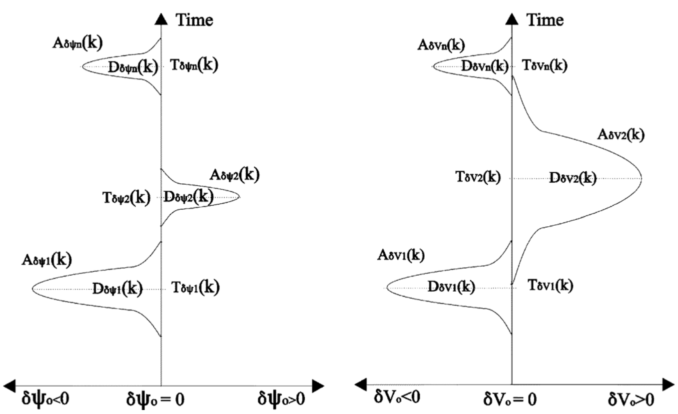

Fig. 11. Course and speed CAAF.

execution. $D_{\delta\psi i}(k), D_{\delta V i}(k)$ and $A_{\delta\psi i}(k), A_{\delta V i}(k)$ represent the course and speed change decisions and actions at the kth instant, respectively. An overview of the SAF module is also presented in Fig. 3. The SAF module consists of two units: course action formation unit and speed action formation unit. The main objective of these two units is to formulate the collision avoidance course and speed control actions.

B. Bayesian Network

A Bayesian network approach is proposed as the inference media between collision avoidance decisions and collision avoidance actions. A Bayesian network can be defined as a data structure that represents the dependencies among variables and gives a concise specification of any full joint probability distribution [43]. The main advantages of the Bayesian network inference approach are the use of prior knowledge and the continuous knowledge update. The topology of the Bayesian network consists of several nodes and links. The links specify the conditional relationship among the nodes in the network.

The continuous Bayesian network module that is formulated to update the parallel collision avoidance decisions into the sequential actions is presented in Fig. 12. The Bayesian network consists of four nodes: collision time estimation, collision risk, actions delay, and collision avoidance actions. The inputs of the Bayesian network are the collision decisions $D_i(k)$ and the time until the collision situation $T_i(k)$ is generated, respectively, by the PDM and CRA modules.

The main objective of the collision time estimation node is to estimate the time until the collision situation $T_i(k)$ between

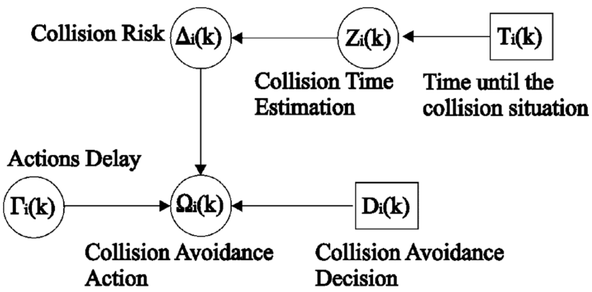

Fig. 12. Bayesian network structure for collision avoidance.

the own vessel and each of the target vessels. The node collision risk inferences the collision risk with respect to each target vessel considering the collision time estimation. The actions delay node is designed to formulate the appropriate time to take collision avoidance actions. The collision avoidance action node is inferenced by the three nodes: actions delay, collision risk, and collision decisions, as presented in Fig. 12. The nodes, their inference, and associated functions are further described in the following sections.

C. Collision Risk Functions

The collision risk function (CRF) of the own vessel $(\Delta_i(k))$ due to the ith target vessel in the kth instant is modeled as a Gaussian distribution $\Delta_i(k) \sim N(\mu_{\Delta i}(k), \sigma^2_{\Delta i}(k))$, with the mean value $\mu_{\Delta i}(k)$ that is estimated by the time until the collision situation $T_i(k)$. The time until the collision situation $T_i(k)$ can be defined as

$$T_i(k) = \mu_{\Delta i}(k) = \frac{|OA_i(k)|}{|V_{i,o}(k)|} \tag{1}$$

where $|OA_i(k)|$ is the relative range and $V_{i,o}(k)$ is the relative speed of the ith target vessel with respect to the own vessel at the kth instant. Further, the covariance $\sigma^2_{\Delta i}(k)$ is considered in this distribution. It is assumed that the CRF $\Delta_i(k)$ can be obtained from the noisy observation function of $Z_i(k)$ and can be written as

$$Z_i(k) = \Delta_i(k) + \omega_{zi}(k) \tag{2}$$

where $\omega_{zi}(k) \sim N(0, \sigma^2_z(k))$ is a Gaussian observation noise with the mean, 0, and the constant covariance $\sigma^2_z(k)$. Hence, the prior distribution of the CRF due to the ith target vessel at the kth instant can be written as a Gaussian distribution

$$P(\Delta_i(k)) = {}^1\alpha_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-\mu_{\Delta i}(k))^2}{\sigma^2_{\Delta i}(k)}\right)} \tag{3}$$

where ${}^1\alpha_i$ is the normalization constant. The transition model of the CRF is considered as a Gaussian perturbation with the constant covariance σ^2_Δ to the current states of the CRF and can be written as

$$P(\Delta_i(k) \,|\, \Delta_i(k-1)) = {}^2\alpha_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-\Delta_i(k-1))^2}{\sigma^2_\Delta}\right)} \tag{4}$$

where ${}^2\alpha_i$ is the normalization constant. The conditional observation model for collision risk is assumed to be a Gaussian distribution with the constant covariance σ_z^2 and can be written as

$$P(Z_i(k)\,|\,\Delta_i(k)) = {}^3\alpha_i e^{-\frac{1}{2}\left(\frac{(Z_i(k)-\Delta_i(k))^2}{\sigma_z^2}\right)} \tag{5}$$

where ${}^3\alpha_i$ is the normalization constant. The one step predicted distribution of the CRF can be written as (6), shown at the bottom of the page.

Considering the Bayesian rule, the CRF update from the observations can be written as

$$\begin{aligned}
&P(\Delta_i(k)|Z_i(k))\\
&= P(Z_i(k)|\Delta_i(k))P(\Delta_i(k))\\
&= {}^3\alpha_i e^{-\frac{1}{2}\left(\frac{(Z_i(k)-\Delta_i(k))^2}{\sigma_z^2}\right)} {}^1\alpha_i{}^2\alpha_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-\mu_{\Delta i}(k-1))^2}{\sigma_\Delta^2+\sigma_{\Delta i}^2(k-1)}\right)}\\
&= {}^1\alpha_i{}^2\alpha_i{}^3\alpha_i e^{-\frac{1}{2}\left(\frac{\left(\Delta_i(k)-\frac{Z_i(k)(\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2).+\mu_{\Delta i}(k-1)\sigma_z^2}{\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2+\sigma_z^2}\right)^2}{\frac{(\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2)\sigma_z^2}{\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2+\sigma_z^2}}\right)}.
\end{aligned} \tag{7}$$

Hence, the updated mean and covariance values of the CRF can be written as

$$\begin{aligned}
\mu_{\Delta i}(k) &= \frac{Z_i(k)\left(\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2\right).+\mu_{\Delta i}(k-1)\sigma_z^2}{\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2+\sigma_z^2}\\
\sigma_{\Delta i}^2(k) &= \frac{\left(\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2\right)\sigma_z^2}{\sigma_{\Delta i}^2(k-1)+\sigma_\Delta^2+\sigma_z^2}.
\end{aligned} \tag{8}$$

A detailed mathematical discussion on derivation of the Gaussian distributions in a general situation is presented in [43].

D. Collision Avoidance Action Function

The own vessel collision avoidance action function (CAAF) is modeled as a Gaussian distribution $\Omega_i(k) \sim N(\mu_{\Omega i}(k), \sigma_{\Omega i}^2(k))$ with the mean $\mu_{\Omega i}(k)$ and the covariance $\sigma_{\Omega i}^2(k)$. The CAAF with respect to the CRF can be written as

$$\Delta_i(k) = \Omega_i(k) + \Gamma_i(k) \tag{9}$$

where $\Gamma_i(k) \sim N(\mu_\Gamma, \sigma_\Gamma^2)$ is the time delay function that is approximated by a Gaussian distribution with the constant mean μ_Γ and the covariance σ_Γ^2. The conditional mean and covariance values of the CRF with respect to the CAAF can be written as

$$\begin{aligned}
E(\Delta_i(k)\,|\,\Omega_i(k)) &= \mu_{\Omega i}(k) + E(\Gamma_i(k)\,|\,\Omega_i(k))\\
&= \mu_{\Omega i}(k) + \mu_\Gamma
\end{aligned} \tag{10}$$

$$\begin{aligned}
V(\Delta_i(k)\,|\,\Omega_i(k)) &= V(\Gamma(k)\,|\,\Omega_i(k))\\
&= V(\Omega_i(k))\\
&= \sigma_\Gamma.
\end{aligned} \tag{11}$$

The conditional CRF with respect to the CAAF as a Gaussian distribution can be written as

$$P(\Delta_i(k)\,|\,\Omega_i(k)) = {}^3\beta_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-(\mu_{\Omega i}(k)+\mu_\Gamma))^2}{\sigma_\Gamma^2}\right)} \tag{12}$$

where ${}^3\beta_i$ is the normalization constant. The prior distribution of the CAAF due to the ith target vessel at the kth instant can be written as a Gaussian distribution

$$P(\Omega_i(k)) = {}^1\beta_i e^{-\frac{1}{2}\left(\frac{(\Omega_i(k)-\mu_{\Omega i}(k))^2}{\sigma_{\Omega i}^2(k)}\right)} \tag{13}$$

where ${}^1\beta_i$ is the normalization constant. The transition model of the CAAF considered as a Gaussian perturbation with the constant covariance σ_Ω^2 to the current states of the CAAF can be written as

$$P(\Omega_i(k)\,|\,\Omega_i(k-1)) = {}^2\beta_i e^{-\frac{1}{2}\left(\frac{(\Omega_i(k)-\Omega_i(k-1))^2}{\sigma_\Omega^2}\right)} \tag{14}$$

where ${}^2\beta_i$ is the normalization constant. The one step predicted distribution of the CAAF can be written as (15), shown at the bottom of the next page. One can recognize (15) as

$$P(\Omega_i(k)) = {}^1\beta_i{}^2\beta_i e^{-\frac{1}{2}\left(\frac{((\Omega_i(k)+\mu_\Gamma)-(\mu_{\Omega i}(k-1)+\mu_\Gamma))^2}{\sigma_\Omega^2+\sigma_{\Omega i}^2(k-1)}\right)}. \tag{16}$$

$$\begin{aligned}
P(\Delta_i(k)) &= \int_{-\infty}^{\infty} P(\Delta_i(k)\,|\,\Delta_i(k-1))P(\Delta_i(k-1))d\Delta_i(k-1)\\
&= \int_{-\infty}^{\infty} {}^2\alpha_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-\Delta_i(k-1))^2}{\sigma_\Delta^2}\right)} {}^1\alpha_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k-1)-\mu_{\Delta i}(k-1))^2}{\sigma_{\Delta i}^2(k-1)}\right)} d\Delta_i(k-1)\\
&= {}^1\alpha_i{}^2\alpha_i \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{\sigma_{\Delta i}^2(k-1)(\Delta_i(k)-\Delta_i(k-1))^2+\sigma_\Delta^2(\Delta_i(k-1)-\mu_{\Delta i}(k-1))^2}{\sigma_\Delta^2\sigma_{\Delta i}^2(k-1)}\right)} d\Delta_i(k-1)\\
&= {}^1\alpha_i{}^2\alpha_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-\mu_{\Delta i}(k-1))^2}{\sigma_\Delta^2+\sigma_{\Delta i}^2(k-1)}\right)}
\end{aligned} \tag{6}$$

Considering the Bayesian rule, the CAAF update from the CRF can be written as (17), shown at the bottom of the page. Hence, the updated mean and covariance values for the updated CAAF can be written as

$$\mu_{\Omega i}(k) = \frac{\Delta_i(k)\left(\sigma^2_{\Omega i}(k-1)+\sigma^2_{\Omega}\right)+(\mu_{\Omega i}(k-1)+\mu_\Gamma)\sigma^2_\Gamma}{\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega+\sigma^2_\Gamma} - \mu_\Gamma$$
$$\sigma^2_{\Omega i}(k) = \frac{\left(\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega\right)\sigma^2_\Gamma}{\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega+\sigma^2_\Gamma}. \tag{18}$$

E. Implementation of Collision Avoidance Actions

The implementation of the accumulated CAAF $A_i(k)$ is divided into two sections of the course control $(A_{\delta\psi i}(k))$ and speed control $(A_{\delta V i}(k))$ CAAFs, as presented in Fig. 11. The CAAFs are generated from the collision avoidance decisions of $D_i(k)$ from the course control decisions $(D_{\delta\psi i}(k))$ and the speed control decisions $(D_{\delta V i}(k))$, as described previously. Hence, the accumulated CAAFs of course control $(A_{\delta\psi}(k))$ and speed control $(A_{\delta V}(k))$ can be written as

$$A_{\delta\psi}(k) = \sum_{i=1}^{n} A_{\delta\psi i}(k) = \sum_{i=1}^{n} D_{\delta\psi i}(k) P(\Omega_{\psi i}(k)\,|\,\Delta_{\psi i}(k))$$
$$A_{\delta V}(k) = \sum_{i=1}^{n} A_{\delta V i}(k) = \sum_{i=1}^{n} D_{\delta V i}(k) P(\Omega_{V i}(k)\,|\,\Delta_{V i}(k)). \tag{19}$$

These accumulated CAAFs are implemented in the computational simulations. The mean and covariance values for the CRF and the CAAFs are updated using (8) and (19).

VI. Computational Simulations

The computational simulations have been implemented on a MATLAB software platform. The sampling time of 1 s has been used for the computational simulations. It is assumed that the target vessels are moving with the constant course and speed conditions and do not honor any navigation rules and regulations of the sea. The constant course and speed conditions are assumed to keep the consistence in the collision situation. One should note that the slight change of the course and speed conditions of the target vessel can remove the collision risk, therefore the effectiveness of the proposed CAS cannot be evaluated.

In this study, two multivessel collision situations are simulated. The multivessel collision situation I, where three target vessels are evolved with three collision situations, is considered. The multivessel collision situation II, where three target vessels are evolved with two collision situations, is considered. Therefore, the CAS performances under the complex navigation conditions are evaluated, as described in the following sections.

A. Multivessel Collision Situation I

The computational simulations for the multivessel collision situation I are presented in Figs. 13–22. As presented in Fig. 13, the own vessel starts navigation from the origin (0 m, 0 m) and the first, second, and third target vessels start from positions (6000 m, −6000 m), (8800 m, 10 000 m), and (−13 200 m, 12 000 m), respectively. All startup and final positions of the own and target vessels are represented by vessel shape icons at the kth instant in the figures. The CRF is presented in the $x = -12\,000$ m axis. Similarly, the CAAFs for the course and speed changes are presented in the $x = -9000$ m and

$$\begin{aligned}
P(\Omega_i(k)) &= \int_{-\infty}^{\infty} P(\Omega_i(k)|\Omega_{i-1}(k))P(\Omega_{i-1}(k))d\Omega_i(k-1) \\
&= \int_{-\infty}^{\infty} {}^1\beta_i e^{-\frac{1}{2}\left(\frac{(\Omega_i(k)-\Omega_i(k-1))^2}{\sigma^2_\Omega}\right)} {}^2\beta_i e^{-\frac{1}{2}\left(\frac{(\Omega_i(k-1)-\mu_{\Omega i}(k-1))^2}{\sigma^2_{\Omega i}(k-1)}\right)} d\Omega_i(k-1) \\
&= {}^1\beta_i {}^2\beta_i \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{\sigma^2_{\Omega i}(k-1)(\Omega_i(k)-\Omega_i(k-1))^2+\sigma^2_\Omega(\Omega_i(k-1)-\mu_{\Omega i}(k-1))^2}{\sigma^2_\Omega\sigma^2_{\Omega i}(k-1)}\right)} d\Omega_i(k-1) \\
&= {}^1\beta_i {}^2\beta_i e^{-\frac{1}{2}\left(\frac{(\Omega_i(k)-\mu_{\Omega i}(k-1))^2}{\sigma^2_\Omega+\sigma^2_{\Omega i}(k-1)}\right)}.
\end{aligned} \tag{15}$$

$$\begin{aligned}
&P(\Omega_i(k)\,|\,\Delta_i(k)) \\
&\quad = P(\Delta_i(k)\,|\,\Omega_i(k))P(\Omega_i(k)) \\
&\quad = {}^1\beta_i e^{-\frac{1}{2}\left(\frac{(\Delta_i(k)-(\mu_{\Omega i}(k)+\mu_\Gamma))^2}{\sigma^2_\Gamma}\right)} {}^2\beta_i {}^3\beta_i e^{-\frac{1}{2}\left(\frac{((\Omega_i(k)+\mu_\Gamma)-(\mu_{\Omega i}(k-1)+\mu_\Gamma))^2}{\sigma^2_\Omega+\sigma^2_{\Omega i}(k-1)}\right)} \\
&\quad = {}^1\beta_i {}^2\beta_i {}^3\beta_i e^{-\frac{1}{2}\left(\frac{\left((\Omega_i(k)+\mu_\Gamma)-\frac{\Delta_i(k)\left(\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega\right)+(\mu_{\Omega i}(k-1)+\mu_\Gamma)\sigma^2_\Gamma}{\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega+\sigma^2_\Gamma}\right)^2}{\frac{(\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega)\sigma^2_\Gamma}{\sigma^2_{\Omega i}(k-1)+\sigma^2_\Omega+\sigma^2_\Gamma}}\right)}.
\end{aligned} \tag{17}$$

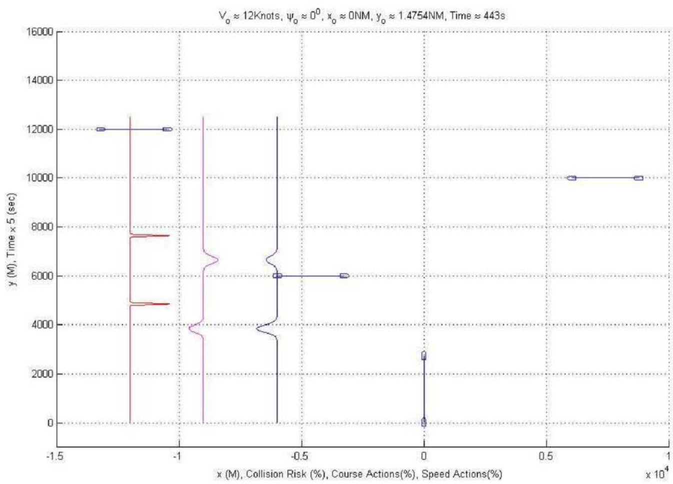

Fig. 13. Simulations of multivessel collision situation I.

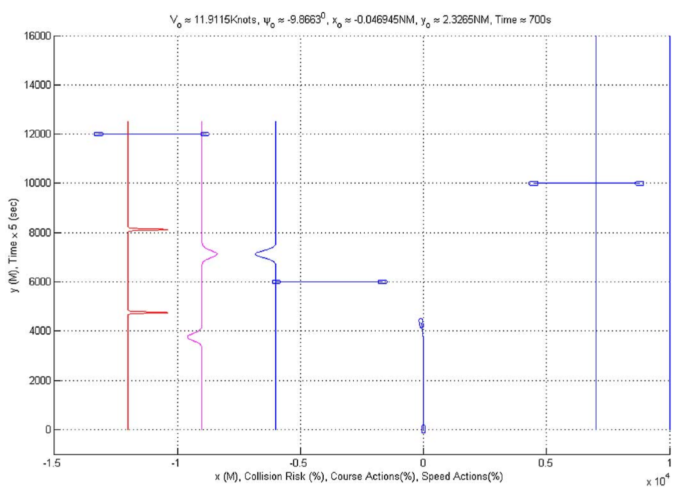

Fig. 14. Simulations of multivessel collision situation I.

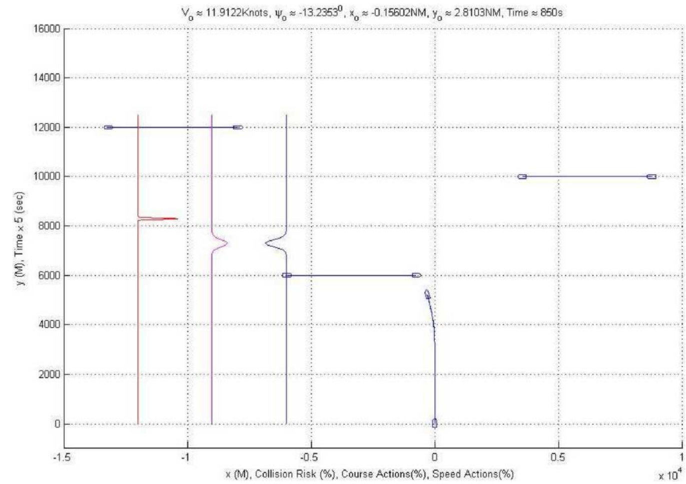

Fig. 15. Simulations of multivessel collision situation I.

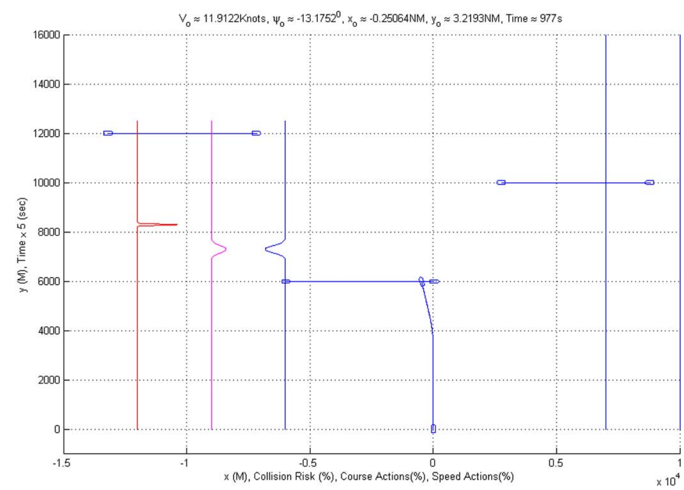

Fig. 16. Simulations of multivessel collision situation I.

$x = -6000$ m axis, respectively. The scaled time axis [5 × actual time (s)] is presented in the y-axis, and the scaled collision risk (the CRF), the CAAFs of course, and speed actions are presented in the x-axis.

In Fig. 13, the CAS has observed two possible collision situations and the accumulated CRF is presented in the $x = -12\,000$ m axis as two peaks in different instants. Furthermore, the respective accumulated CAAFs of course and speed with respect to each collision situation are presented in the same figure in the axis of $x = -9000$ m and $x = -6000$ m. The accumulated CAAFs, alter course to port and reduce speed, to avoid the first target vessel and, alter course to starboard and reduce speed, to avoid the second target vessel, are also presented in the same figure.

Fig. 14 presents the subcompletion of the first action segment of the CAAFs, consisting in speed reduction and continuation of the course change to port by the own vessel. In Fig. 15, the own vessel is about to safely pass the first target vessel on completion of the first action segment of the CAAFs. In Fig. 16, the own vessel passes the first target vessel safely.

In Fig. 17, the own vessel is about to face the second target vessel with the CAAFs indicating alter course to starboard and reduce speed. After the execution, the CRF is reduced for the second target vessel, as shown in Fig. 18. However, the third target vessel is detected. The respective collision avoidance conditions, the CRF and the CAAFs, are also presented in the same figure. Further, safe passing of the second target vessel is presented in Fig. 19.

Fig. 20 presents on completion of the execution of the CAAFs to avoid the third target vessel, consisting in speed reduction and continuing the course change to port. Finally, the completion of all the CAAFs with negligible collision risk and safe passing of the third target vessel are presented in Figs. 21 and 22, respectively. One should note that the first and second target vessels navigate as the "give way" vessels that do not take any appropriate actions to avoid the collision situations. Hence, the own vessel even as the "stand on" vessel takes appropriate actions to avoid collisions as recommended by the COLREGs rules and regulations.

B. Multivessel Collision Situation II

The computational simulations for the multivessel collision situation II are presented in Figs. 23–31. As presented in Fig. 23, the own vessel starts navigation from the origin (0 m, 0 m) and

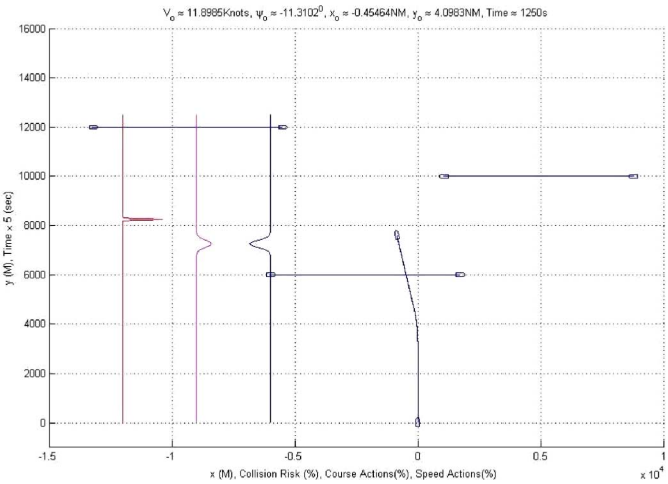

Fig. 17. Simulations of multivessel collision situation I.

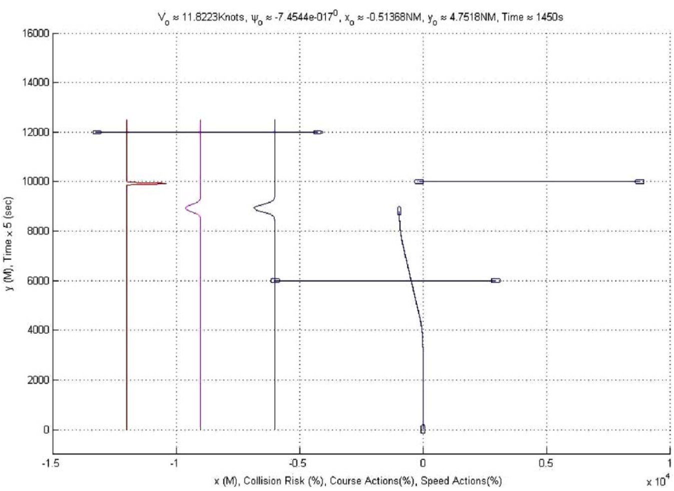

Fig. 18. Simulations of multivessel collision situation I.

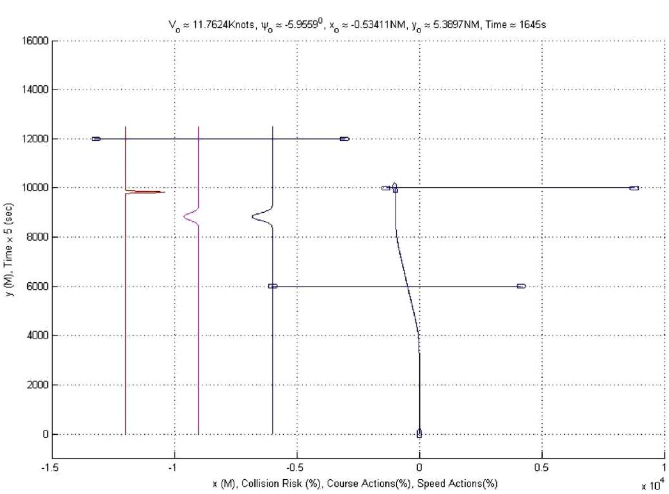

Fig. 19. Simulations of multivessel collision situation I.

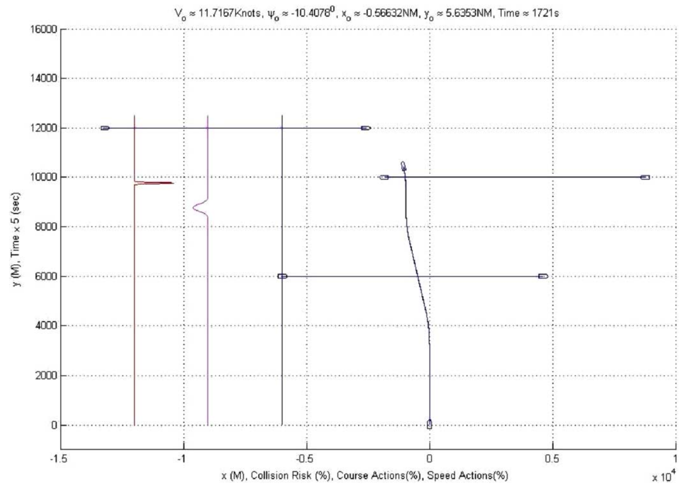

Fig. 20. Simulations of multivessel collision situation I.

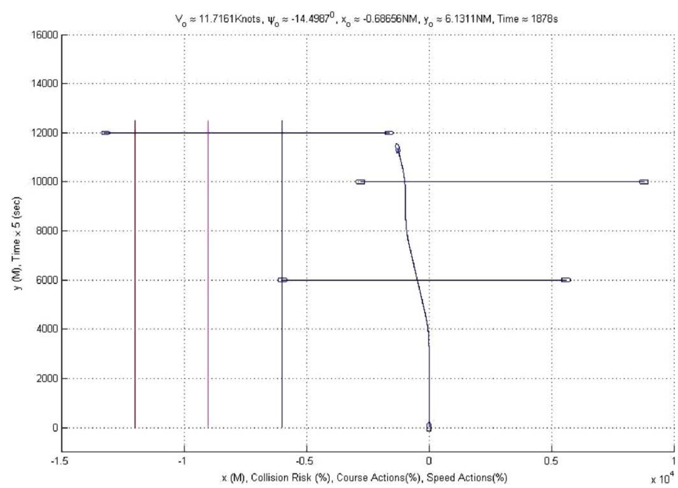

Fig. 21. Simulations of multivessel collision situation I.

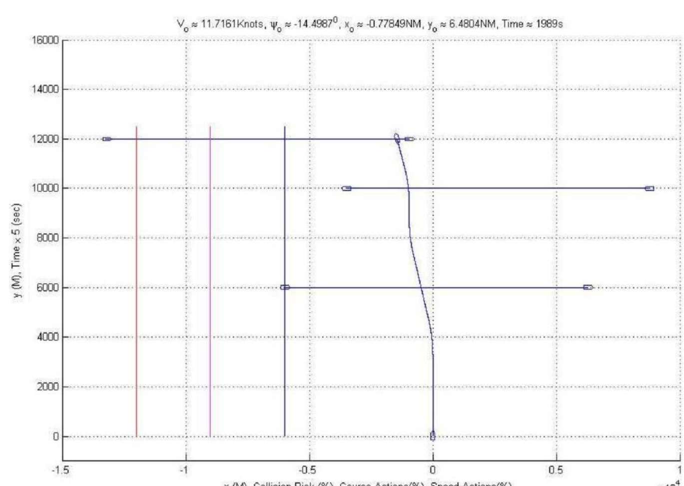

Fig. 22. Simulations of multivessel collision situation I.

the first, second, and third target vessels start from positions (6000 m, -6000 m), (-5000 m, 670 m), and ($-11\,220$ m, 5000 m), respectively. Similarly, all startup and final positions of the own and target vessels are presented by vessel shape icons at the kth instant in the figure. The CRF assessment is presented in the $x = -12\,000$ m axis. Similarly, the CAAFs for the course and speed changes are presented in the $x = -9000$ m and $x = -6000$ m axis, respectively. The scaled time axis [5 $\times$ actual

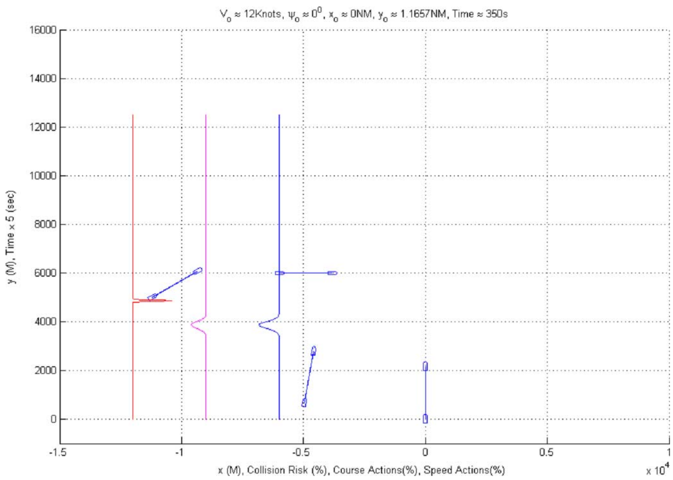

Fig. 23. Simulations of multivessel collision situation II.

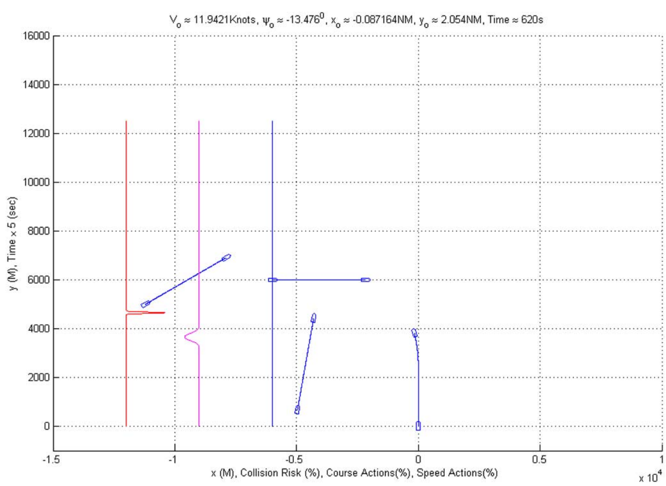

Fig. 24. Simulations of multivessel collision situation II.

time (s)] is presented in the y-axis, and the scaled collision risk (the CRF), the CAAFs of course, and speed actions are also presented in the x-axis.

In Fig. 23, the CAS has observed two possible collision situations and the accumulated CRF is presented in the $x = -12\,000$ m axis as one peak in an instant. Furthermore, the respective accumulated CAAFs of course and speed, with respect to the collision situation, are presented in the same figure in the axis of $x = -9000$ m and x $= -6000$ m. The accumulated CAAFs, alter course to port and reduce speed, to avoid the first target vessel, are also presented in the same figure.

Fig. 24 presents the subcompletion of the first action segment of the CAAFs, consisting in speed reduction and continuation of the course change to port side by the own vessel. Fig. 25 presents the completion of the first action segment of the CAAFs. In Fig. 26, the own vessel is about to safely pass the first target vessel. Fig. 27 presents the instant when the own vessel passes the first target vessel safely with the CAAFs indicating the course change to port and speed reduction. However, one should note that the CRF indicates the collision risk due to the third target vessel. This is due to the noncollision situation with the second target vessel as it is moving away from the own

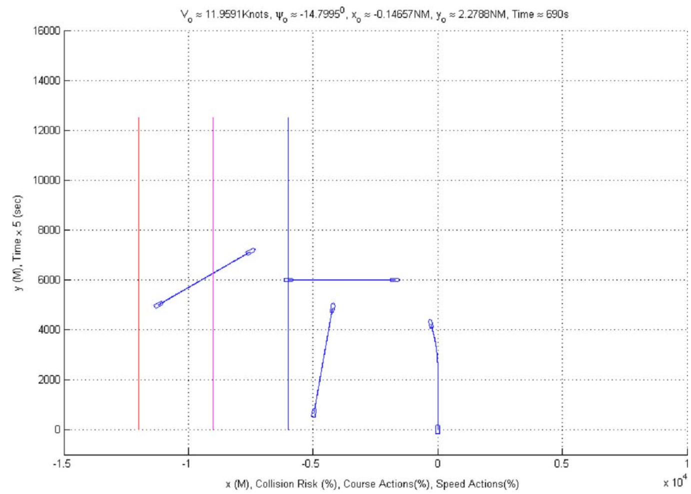

Fig. 25. Simulations of multivessel collision situation II.

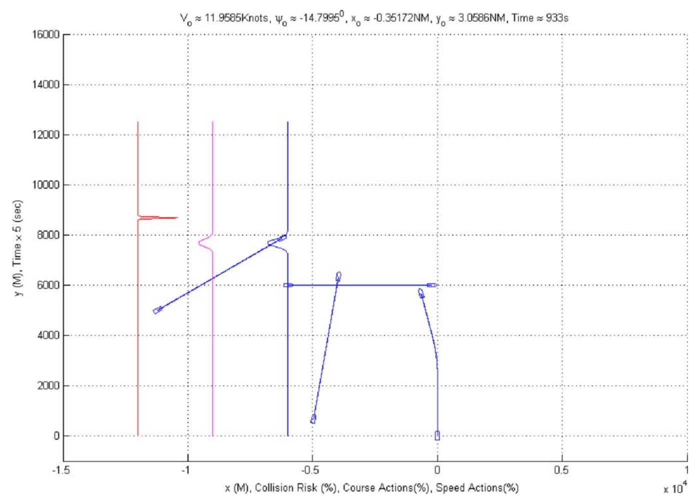

Fig. 26. Simulations of multivessel collision situation II.

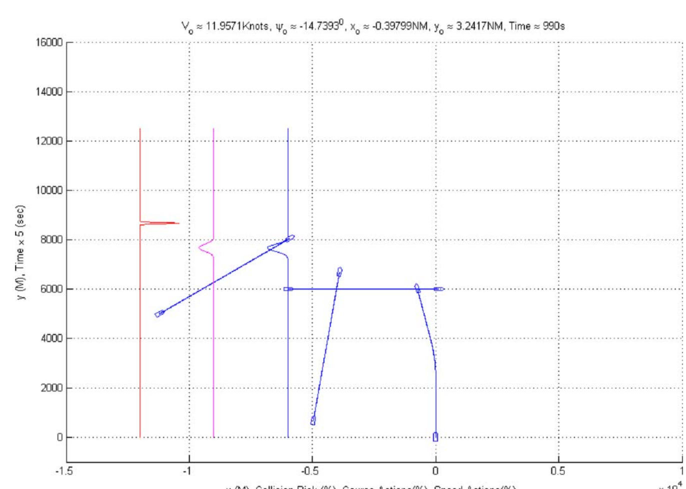

Fig. 27. Simulations of multivessel collision situation II.

vessel. Fig. 28 presents the subcompletion of the second action segment of the CAAFs, consisting in speed reduction and continuation of the course change to port by the own vessel. Finally, the completion of all the CAAFs with negligible collision risk

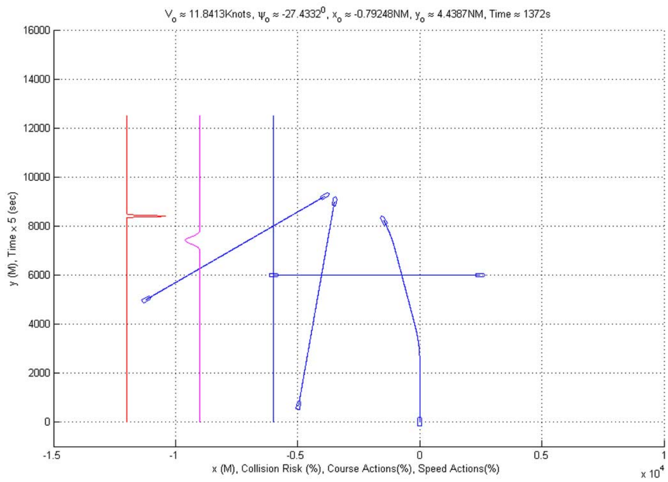

Fig. 28. Simulations of multivessel collision situation II.

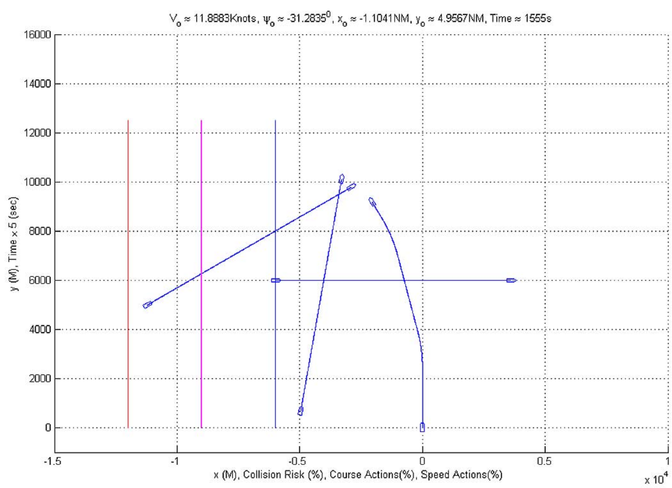

Fig. 29. Simulations of multivessel collision situation II.

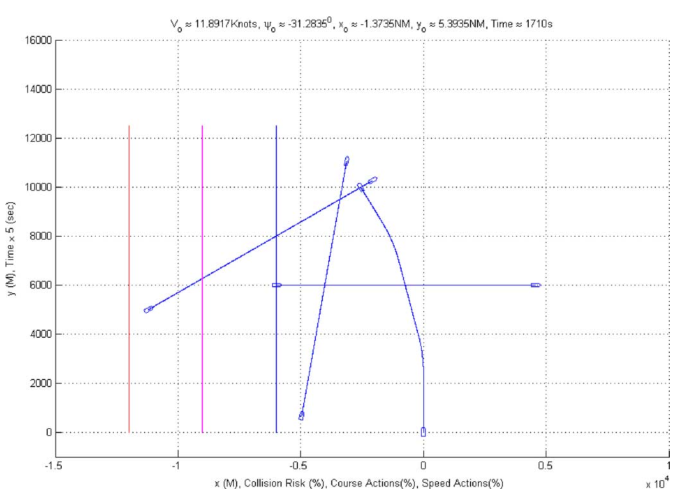

Fig. 30. Simulations of multivessel collision situation II.

and safe passing of the second and third target vessels are presented in Figs. 29, 30, and 31, respectively.

One should note that the trajectories of the second and third vessels in this simulation are heading for the same intersection point. However, only one of the vessels is approaching for a collision with the own vessel. Therefore, the proposed CAS takes appropriate actions to avoid the collision-risk-generated target vessel, and the noncollision-risk-generated target vessel is ignored. This is another advantage in the proposed CAS.

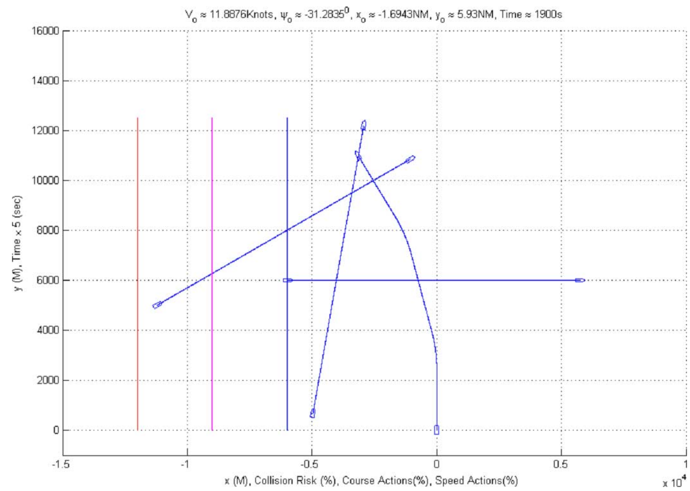

Fig. 31. Simulations of multivessel collision situation II.

As noted from both simulations, the own vessel has taken both course and speed change decisions/actions to avoid collision situations. However, this has not been common practice in ocean navigation, where the course change is a preferred method of collision avoidance among vessels. Therefore, the slight speed changes and the larger course changes are considered in the action execution process in this study, where the speed change CAAF is decreased faster in comparison to the course change CAAF in the collision avoidance situations. However, the COLREGs rules and regulations insist on taking any measures necessary to avoid the collision situation. Therefore, the change of speed of the own vessel during a collision situation should be preformed.

VII. Conclusion and Future Work

This paper introduces a novel method to implement complete decisions formulation and action execution process of collision avoidance in ocean navigation. As presented in the computational simulations, the fuzzy-Bayesian-based decision/action formulation process is used to avoid complex collision situations in ocean navigation. The successful results obtained in this study show the CAS capabilities of collision avoidance involving multiple vessels in ocean navigation while still respecting the COLREGs.

However, there are various parameters that are introduced in this study as constants in the CRF and the CAAFs. These parameters are somewhat related to the navigation characteristics of the own vessel as well as the navigation sensor capabilities (i.e., radar and laser systems). Therefore, further studies should be developed to improve the identification of the parameters of the CRF and the CAAF of the Bayesian network module. In addition, similar parameter identifications should be formulated to optimize the fuzzy-logic-based PDM module and the Bayesian-network-based SAF module.

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